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COVID-19 and stock market volatility: An industry level analysis

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ABSTRACT

COVID-19 has had significant impact on US stock market volatility. This study focuses on understanding the regime change from lower to higher volatility identified with a Markov Switching AR model. Utilizing machine learning feature selection methods, economic indicators are chosen to best explain changes in volatility. Results show that volatility is affected by specific economic indicators and is sensitive to COVID-19 news. Both negative and positive COVID-19 information is significant, though negative news is more impactful, suggesting a negativity bias. Significant increases in total and idiosyncratic risk are observed across all industries, while changes in systematic risk vary across industry.

1. Introduction

We are in the midst of one of the largest pandemics in history, COVID-19; originating in China it has migrated across the globe. Investors and markets are facing a high degree of uncertainty regarding both physical and financial impacts of the virus. The recent Coronavirus (COVID-19) outbreak has resulted in unprecedented volatility in the U.S. financial markets. For example, CBOE Volatility Index (VIX)[1] surged over 80 on 16th March 2020, surpassing its 2008 record. S&P500 and Nasdaq Composite indices dropped by 12 per cent on 16th March 2020. On the same day, the Wall Street Journal reported that Dow Jones Industrial Average (DJIA) dropped over 12 per cent '*marking the second-worst day in its 124-year history. But those reasons do not fully explain the remarkable volatility*.'

Previous research has focused on the impact of pandemics such as SARS and EBOLA (Goodell, 2020; Chen et al., 2007, 2009; Baker et al., 2012; Wang et al., 2013; Bai, 2014; Del Giudice and Paltrinieri, 2017; Chen et al., 2018; Ichev and Marinč, 2018) on stock market performance. Given the enormity of the current pandemic, researchers have begun to examine the impact of COVID-19 and a clear pattern has emerged. Ashraf (2020) shows a correlation between growth in COVID-19 and poor stock market performance across 64 countries. An inverse relationship between real time changes in COVID-19 infection projections and US stock performance exists (Alfaro et al., 2020). Event studies for key COVID-19 milestones show international stock markets were negatively impacted (Heyden and Heyden, 2020; Liu et al., 2020).

Volatility is critical to the operation of financial markets. It acts as a barometer of financial risk or uncertainty surrounding

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[1] VIX is a closely watched measure of volatility in U.S. stocks.

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investments in financial assets and, therefore, it is of natural interest to individual investors, mutual fund managers, financial industry regulators as well as policymakers. Few studies have established a link between the COVID-19 pandemic and financial market volatility. Attempts to understand the effect of COVID-19 on market volatility include a study by Baker et al. (2020), which identifies the current pandemic as having the greatest impact on stock market volatility in the history of pandemics. It also identifies government limitations on commercial activity and restrictions on consumers as the explanation for increased volatility. Zaremba et al. (2020) examine if government response to COVID-19 mitigates international stock market volatility. They document a significant increase in stock market volatility in countries where governments take rigorous actions to curb the spread of COVID-19, such as information campaigns and cancellation of public events. Further, Onali (2020) identified significant increases in volatility for US stock markets in response to reports of COVID-19 cases and deaths in multiple countries. There is potential for variation in volatility across industries, for example, higher rated Environmental and Social firms exhibit lower stock return volatility (Albuquerque et al., 2020). Notably, Haroon and Rizvi (2020) investigate whether COVID-19 news coverage leads to shifts in volatility. They identify changes in volatility, with the strongest impact on transportation, automobile, energy and travel & leisure industries. But the majority of industries they examined did not exhibit significant shifts in volatility as a result of media coverage and news sentiment.

This study adds to the scant literature on understanding the impact of COVID-19 pandemic on the US stock market volatility (Zaremba et al., 2020; Baker et al., 2020; Zhang et al., 2020; and Haroon and Rizvi, 2020). In this paper, we extend on limited COVID-19 research in several dimensions. First, we quantify the volatility in three measures of risk in the COVID-19 period: total, market and idiosyncratic. Second, we use a Markov Switching AR Model to identify regime change from a lower to higher volatility. Third, we use machine learning (ML) feature selection methods to identify data patterns and most influential economic indicators to explain changes in volatility. Fourth, while aggregated index level analysis assumes homogeneity in stock market return and volatility, the equity returns and its volatility at the sector level are likely to be heterogeneous (Al-Awadhi et al., 2020; Haroon and Rizvi, 2020; Phan et al., 2015; Rizvi and Arshad, 2018) depending on the extent a particular sector is exposed to COVID-19 pandemic risk. Therefore, we examine whether the impact of dissemination of information regarding COVID-19 varies by industry. Results indicate that industries most impacted by negative aggregate demand shocks, such as petroleum and natural gas, restaurants, hotels and lodgings exhibited the largest increases in risk, whereas industries such as food production, beer and liquor with steady or increased demand exhibited smaller changes. Finally, to our knowledge, this is the first paper to distinguish between dissemination of positive and negative information to determine if market volatility is sensitive to information type. Our investigation is motivated by previous research, which identified that price and volatility spillovers exist across major markets and that volatility spillover stemming from bad news is more pronounced (Koutmos and Booth, 1995).

2. Data and methodology

We explore the US stock market response to daily reporting on COVID-19. Data includes daily U.S. stock index values, macroeconomic indicators and daily number of COVID-19 cases from 2nd January 2020 to 30th April 2020. The number of COVID-19 confirmed cases, deaths and recoveries are collected from the Johns Hopkins Coronavirus Resource Center.[2] Daily economic variables are obtained from the FRED[3] database. We collected 30 industry stock returns from the Kenneth French data library[4] and stock index values from Bloomberg.

The Markov Switching (MS) regime AR (1) model (Hamilton and Susmel, 1994)[5] is used to identify structural changes in volatility for the US stock markets, see Fig. 1. The MS-AR(1) results in panel (a) show two distinct regimes: a low and high period. CRSP Value Weighted (VW) market index returns in panel (b) show the US stock market shifted to a high volatility state with the spread of COVID-19, beginning 24th February 2020. Fig. 2 panels show that all economic indicators examined display sizeable sensitivity to the spread of COVID-19. The WTI Crude Oil Prices (WTI), Federal Target Range (FTR), Overnight LIBOR (LIBOR) and Effective Federal Fund Rate (EFFR) sharply declined. The remaining indicators steeply soared, reflecting greater uncertainty regarding the impact of COVID-19. To examine the shift, we divided our sample into sub-samples as indicated by the MS-AR(1) model: pre-COVID (2nd January 2020 to 23rd February 2020) and COVID-19 (24th February 2020 to 30th April 2020).

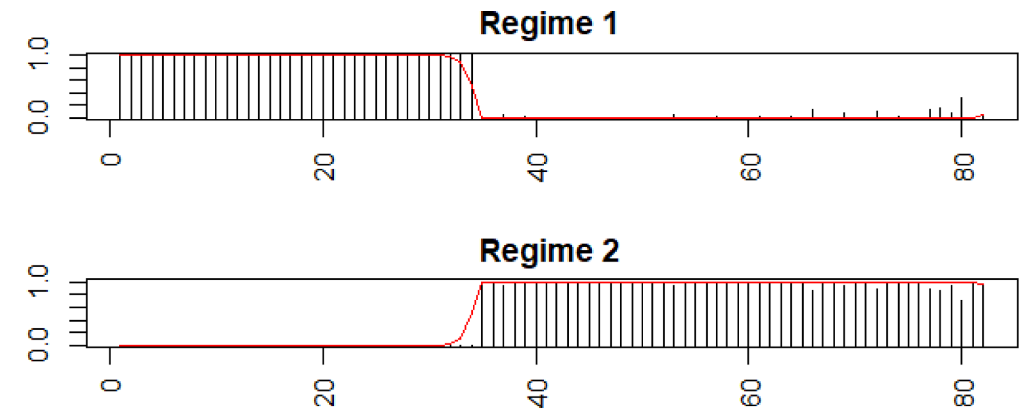
2.1. COVID-19 proxies

In order to capture the effect of daily changes in the spread of COVID-19 on the US stock market, we use daily percentages of both deaths and recoveries. We calculate the percentages of deaths and recoveries at time t in Eq. (1).

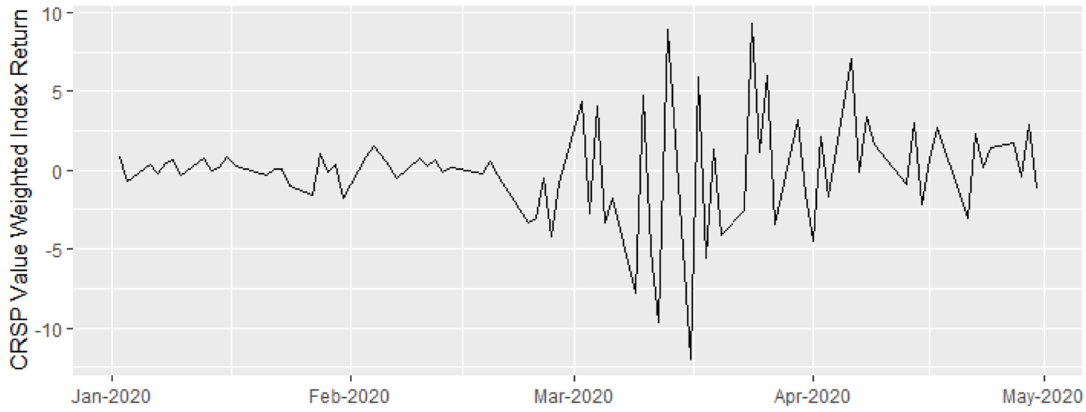
$$\begin{aligned} \%\,of\ deaths(t) &= \frac{Number\ of\ deaths(t)}{Cumulative\ number\ of\ confirmed\ cases(t)} \times 100 \\ \%\,of\ recoveries(t) &= \frac{Number\ of\ recoveries(t)}{Cumulative\ number\ of\ confirmed\ cases(t)} \times 100 \end{aligned} \tag{1}$$

We use these measures as proxies for COVID-19 news; a cursory comparison of the proxy graphs in Fig. 3 and the CBOE VIX graph

[2] Johns Hopkins University of Medicine Coronavirus Resource Center. https://coronavirus.jhu.edu/data
[3] FRED economic data in St. Louis FED. https://fred.stlouisfed.org/
[4] Kenneth R. French data library. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5] The lag length of one in our AR model is based on AIC, SIC, and HQC.



(a) Markov Regime Switching-AR(1) Model



(b) CRSP Value-Weighted Stock Index Return

Fig. 1. CRSP Value Weighted Index Returns and Markov Switching Regimes.

reveals an intriguing pattern. The CBOE VIX is increasing as the percentage of deaths increases and decreasing as the percentage of recoveries increases. To investigate this pattern, we use the percentage of deaths and recoveries as proxies for negative and positive COVID-19 news, respectively.

2.2. Estimating changes in total, systematic and idiosyncratic risk

We studied the impact of COVID-19 on U.S. stock market volatility across 30 industries, measuring daily time-varying total, systematic and idiosyncratic risks, similar to Mohanty et al. (2018). To estimate risks on day t, we used a two-year rolling window from day t to $t - 503$.

Total risk is estimated using the variance of daily stock returns on a 2-year rolling window for each industry:

$$\bar{R}^i{}_{M,t} = \frac{1}{M}\sum_{t=0}^{n-1} R_{M-t}$$
$$\sigma^2_{i,t} = \frac{1}{M}\sum_{t=0}^{n-1}(R^i_{,M-t} - \bar{R}^i{}_{M,t})^2 \tag{2}$$

where $\sigma^2_{i,t}$ represents total risk on day t for industry i, $\bar{R}^i{}_{M,t}$ is an equally weighted mean of the previous M observations, n is the number of a sequence of values, and M is the size of the rolling window. CAPM time-varying betas are used to capture systematic risk ($\beta_{i,t}$) at time t for each industry. We regress the CRSP VW market index on the stock return of industry i for a 2 year rolling basis:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}\ R_{m,t} + \ \epsilon_t \tag{3}$$

where $R_{i,t}$ is the stock return of industry i on day t, $R_{m,t}$ is the return of CRSP VW market index on day t. Idiosyncratic risk ($\sigma^2_{\epsilon\, i,t}$), is measured by the variance of the residual in Eq. (3).

Utilizing the estimated risk measurements, we determine whether these risks show notable differences between the pre-COVID-19

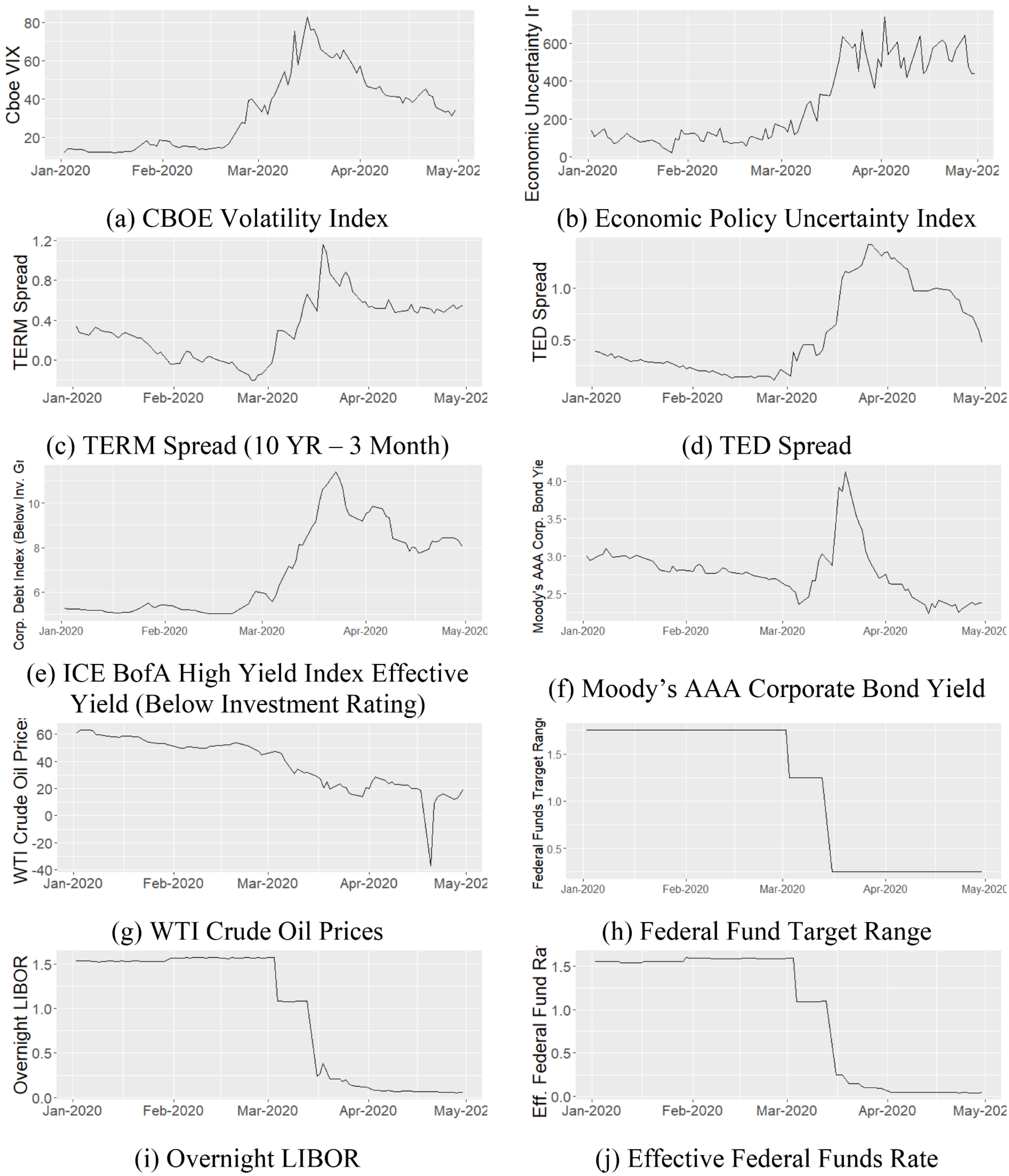
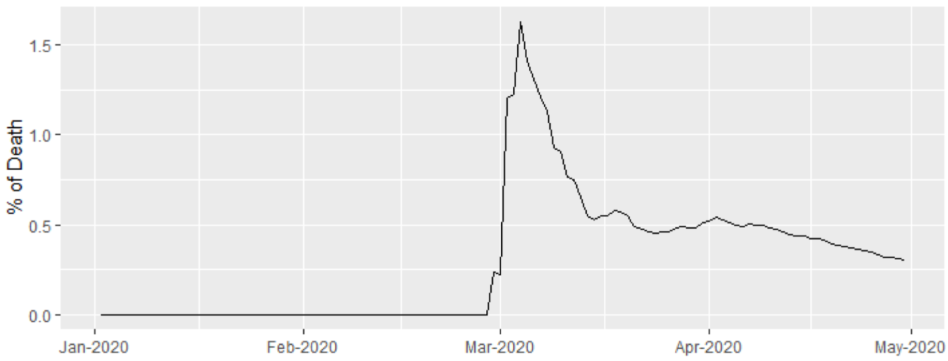


Fig. 2. Daily Economic Indicators from 2nd January 2020 to 23rd February 2020.

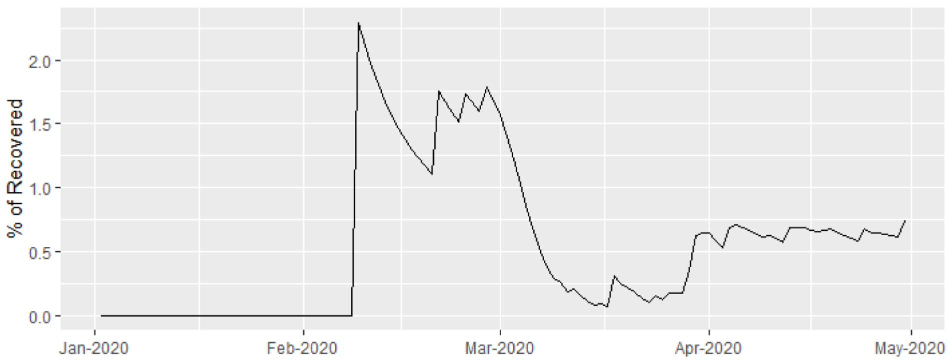
and COVID-19 periods, across 30 industries. We test the hypotheses presented below utilizing *t*-statistics to determine whether the change in risk is significantly different from zero.

$$H_0\text{:}\ \ \Delta\sigma^2 = \bar{\sigma}_C^2 - \bar{\sigma}_{PC}^2$$
$$H_0\text{:}\ \Delta\beta = \bar{\beta}_C - \bar{\beta}_{PC}$$
$$H_0\text{:}\ \ \Delta\sigma_\epsilon^2 = \bar{\sigma}_{\epsilon C}^2 - \bar{\sigma}_{\epsilon PC}^2 \tag{4}$$

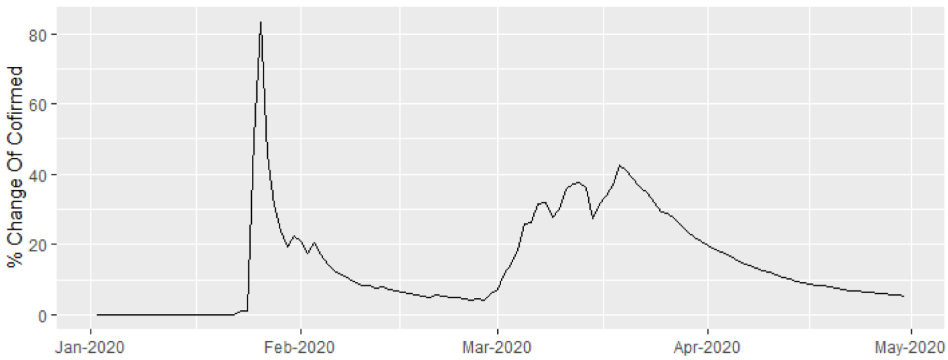
where $\Delta\sigma^2$ is the mean difference in total risk, $\Delta\beta$ is the mean difference in market risk, $\Delta\sigma_\epsilon^2$ is the mean difference in idiosyncratic



(a) Percent of the death in COVID-19



(b) Percent of recovered in COVID-19



(c) Percent change of the number of COVID-19 confirmed

Fig. 3. Daily COVID-19 cases from 2nd January 2020 to 23rd February 2020.

risk, PC is pre-COVID-19 (2nd January 2020 to 23rd February 2020), and C is the COVID-19 period (24th February 2020 to 30th April 2020).

2.3. Machine learning feature selection and estimating changes in risk

We examined to what degree daily economic fundamental measurements and COVID-19 reporting explain the changes of risks in the US stock market. Given that the economic variables are highly correlated,[6] developing a structural linear model with all the

[6] Most of the averages of absolute correlation coefficients, except for Moody's AAA, are greater than 0.74.

Table 1
Feature Selection based on machine learning.

CART-Variable Importance	Genetic Algorithm	Random Forest
VIX	VIX	VIX
(15.53)	(63.3%)	(12.08)
WTI	TED	WTI
(11.88)	(46.7%)	(7.39)
High Yield Bond	Fed Target Range	High Yield Bond Index
(11.12)	(46.7%)	(7.38)
Fed Target Range	EPUI	Fed Target Range
(10.35)	(36.7%)	(2.84)
EPUI	TERM	EPUI
(7.38)	(36.7%)	(2.54)

This table reports the result of feature selection among 10 economic indicators based on the machine learning methods: CART (Decision Tree)-variable Importance, Genetic Algorithm, Random Forest. All the variables are selected based on their importance measures.
Parenthesis in each method represents mean of importance measure, percent of importance measure, and mean of Gini importance score, respectively.

economic variables may include multi-collinearity. Thus, we use machine learning (ML) feature selection methods (CART-Variable Importance, Genetic Algorithm, Random Forest) to identify the most influential economic indicators and classify the pre-COVID and COVID-19 states (Oreski and Oreski, 2014; Liew and Mayster 2018). Table 1 presents the five most influential variables determined using the three ML methods. VIX, Fed Target range and EPUI were identified as influential by all three ML algorithms. However, we focus on VIX and Federal Target Range given our auxiliary regression analysis findings.[7]

A regression model is used to evaluate if changes in economic indicators and daily COVID-19 deaths and recoveries can capture the variation in risks over the sample period:

$$\Delta \mathrm{Risk}_t = \gamma_0 + \gamma_1 \Delta \mathrm{VIX}_t + \gamma_2 \Delta \mathrm{FTR}_t + \gamma_3 \mathrm{pDeaths} + \gamma_4 \mathrm{pRecoveries} + \varepsilon_t \tag{5}$$

where Δ Risk_t is daily change in total risk, $\sigma_t^2 - \sigma_{t-1}^2$, $\Delta \mathrm{VIX}_t$ is daily change in VIX, $\mathrm{VIX}_t - \mathrm{VIX}_{t-1}$, $\Delta \mathrm{FTR}_t$ is daily change in federal reserve target range, $\mathrm{FTR}_t - \mathrm{FTR}_{t-1}$, pDeaths is percent of deaths, and pRecoveries is percent of recoveries.

3. Results

3.1. Changes in risk

Table 2 summarizes total risk for the pre-COVID and COVID-19 regime. Due to space limitation, we only provide results for 14 industries after numbering the industries in the order of difference in total risk between two periods. Panel A reports the top seven industries with the largest mean differences in total risk and panel B presents the bottom seven industries. The *t*-statistics for all 30 industries are greater than 2.0, indicating that total risk in all U.S. industries have significantly increased due to the COVID-19 regime change. Among the 30 industries, we note that the largest shift in total risk is in the petroleum and natural gas industry (increased by 3.92) and restaurants, hotels and lodgings industry (increased by 2.42), while there is a smaller impact on the food production industry (increased by 0.70) and beer and liquor industry (increased by 0.71). Major oil companies experienced sizeable changes in aggregate demand and oil price shocks. Lockdowns in the second quarter of 2020 were widely instituted, limiting travel and reducing the demand for oil consumption, sending crude oil prices tumbling (e.g., Saeed and Gamal, 2020).[8] The substantial impact on industries such as restaurants, hotels, lodgings, games and entertainments, apparel, and transportation may stem from operations more conducive to disease transmission, and consequently more severely impacted by the institution of social distancing and shutdowns (Alfaro et al., 2020). Conversely, industries such as food production, beer and liquor, healthcare, medical, and pharmaceuticals exhibit less exposure to COVID-19. Consumers spending focused on groceries, both conventional and specialty foods experienced increased sales year-over-year.[9] The COVID-19 shock may be mitigated by a greater facility for online or socially distanced operations.

Table 3 summarizes systematic risk exposure during the pre-COVID-19 and COVID-19 regime. Similarly, we sort industries by the difference in market risk exposure between the two periods and present the top seven (panel A) and bottom seven industries (panel B). Interestingly, with the exception of the petroleum and natural gas industry, defensive industry stocks with betas less than 1.00 have the largest market risk increases ranging from 0.12 (telecom and broadcasting) to 0.36 (utilities). While aggressive stocks with

[7] Our auxiliary regression analysis of the change of risk on control variables (including three variables) shows all three selected variables are statistically significant. But we find that the coefficient of EPUI is close to zero and not economically meaningful.
[8] For example, Saeed, A. and R. Gamal, "Saudi Aramco's profit plunges, sees signs of oil market recovery" Reuters, August 9, 2020.
[9] C. Wiley, "Specialty Food Sales Reach $158.4 Billion in 2019, Sales Continue to Rise During COVID-19" Food Industry Executive, July 7, 2020. https://foodindustryexecutive.com/2020/07/specialty-food-sales-reach-158-4-billion-in-2019-sales-continue-to-rise-during-covid-19/

Table 2
Total Risks for the pre-COVID-19 and COVID-19 regime periods.

Industry	$\bar{\sigma}_C^2$	$\bar{\sigma}_{PC}^2$	$\bar{\sigma}_C^2 - \bar{\sigma}_{PC}^2$	*t*-statistics
Panel A: Top 7 industries				
Petroleum and Natural Gas	6.04	2.12	3.92	12.47***
Restaurants, Hotels, & Lodgings	3.17	0.75	2.42	10.42***
Coal	6.48	4.10	2.39	11.98***
Recreation (Games and Entertainments)	4.51	2.70	1.81	10.71***
Apparel	3.49	1.72	1.77	10.00***
Construction & Construction Materials	3.13	1.37	1.75	10.48***
Aircraft, Ships, and Railroad Equipment	3.40	1.70	1.70	10.25***
Panel B: Bottom 7 industries				
Tele-com & Broadcasting	1.96	0.82	1.14	10.68***
Tobacco	3.10	2.02	1.09	11.29***
Personal and Business Services	2.62	1.61	1.01	10.74***
Health Care, Medical, Pharmaceutical Products	2.00	1.02	0.97	10.84***
Business Equipment	2.73	1.78	0.95	10.62***
Beer & Liquor	1.53	0.82	0.71	11.03***
Food Production	1.37	0.67	0.70	11.28***
SP500 Index	1.91	0.87	1.04	11.46***

This table reports means of total risks for pre-covid-19 sample period and COVID-19 sample period, and mean differences in total risks between two sample periods. Panel (a) shows top 7 industries among 30 industries, which have higher mean differences between two sample periods. Panel (b) shows bottom 7 industries have lower mean differences between two sample periods.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 3
Systematic Risks for the pre-COVID-19 and COVID-19 regime periods.

Industry	$\bar{\beta}_C$	$\bar{\beta}_{PC}$	$\bar{\beta}_C - \bar{\beta}_{PC}$	*t*-statistics
Panel A: Top 7 industries				
Utilities	0.65	0.29	0.36	12.74***
Restaurants, Hotels, & Lodgings	0.93	0.68	0.25	11.81***
Tobacco	0.70	0.49	0.21	11.19***
Petroleum and Natural Gas	1.24	1.04	0.20	13.93***
Consumer Goods	0.76	0.58	0.19	12.27***
Food Production	0.63	0.49	0.14	12.83***
Tele-com & Broadcasting	0.81	0.69	0.12	9.68***
Panel B: Bottom 7 industries				
Business Equipment	1.11	1.28	−0.17	−15.91***
Personal and Business Services	1.08	1.22	−0.14	−16.52***
Steel	1.16	1.28	−0.11	−12.96***
Fabricated Products and Machinery	1.18	1.27	−0.1	−16.44***
Electrical Equipment	1.06	1.15	−0.09	−12.25***
Automobiles and Trucks	1.05	1.11	−0.06	−13.92***
Health Care, Medical, Pharmaceutical Products	0.89	0.92	−0.03	−17.91***

This table reports average betas for pre-covid-19 sample period and COVID-19 sample period, and mean differences in the average betas for each industry between two sample periods. Panel (a) shows top 7 industries among 30 industries, which have higher mean difference in average betas between two sample periods. Panel (b) shows bottom 7 industries have lower mean difference in average betas between two sample periods.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

betas greater than 1.00 prior to the COVID-19 pandemic exhibit market risk decreases ranging from 0.06 (automobiles and trucks) to 0.17 (business equipment). Alfaro et al. (2020), find that the firm-level changes in market risk vary across industries and that more capital-intensive, leveraged, and less profitable industries are likely to experience larger shifts in market risk. Shifts in market risk are related to uncertainty regarding the length and extent of shutdowns and the impact on demand.[10] Unsurprisingly, utilities and the oil and gas industry, both capital intensive and highly leveraged, experience some of the largest shifts in market risk.[11]

Table 4 shows that all industries experienced significant increases in idiosyncratic risk from the pre-COVID-19 to COVID-19

[10] For example, while announcing second quarter earnings, Berkshire Hathaway Company warned of the ongoing uncertainty stemming from COVID-19:

"The risks and uncertainties resulting from the pandemic that may affect our future earnings, cash flows and financial condition include the nature and duration of the curtailment or closure of our various facilities and the long-term effect on the demand for our products and services."

[11] Davison (2020) finds that the leverage ratio disproportionately impacts the stock returns of firms that are highly exposed to the economic consequences of social distancing.

Table 4
Idiosyncratic Risks for the pre-COVID-19 and COVID-19 regime periods.

Industry	$\bar{\sigma}^2_{\epsilon C}$	$\bar{\sigma}^2_{\epsilon PC}$	$\bar{\sigma}^2_{\epsilon C} - \bar{\sigma}^2_{\epsilon PC}$	*t*-statistics
Panel A: Top 7 industries				
Petroleum and Natural Gas	2.96	1.14	1.81	11.97***
Coal	4.31	3.06	1.24	13.52***
Restaurants, Hotels, & Lodgings	1.31	0.33	0.98	10.07***
Recreation (Games and Entertainments)	1.59	0.98	0.6	10.08***
Printing and Publishing	1.34	0.89	0.45	9.23***
Metal and Mining	1.56	1.11	0.45	11.20***
Apparel	1.14	0.72	0.42	8.96***
Panel B: Bottom 7 industries				
Transportation	0.64	0.45	0.19	10.72***
Finance	0.37	0.19	0.17	9.16***
Personal and Business Services	0.42	0.25	0.16	11.74***
Business Equipment	0.43	0.28	0.15	13.25***
Beer & Liquor	0.73	0.59	0.14	10.25***
Steel	1.39	1.27	0.12	7.15***
Food Production	0.54	0.45	0.09	11.06***

This table reports means of idiosyncratic risks for pre-covid-19 sample period and COVID-19 sample period, and mean differences in idiosyncratic risks between two sample periods. Panel (a) shows top 7 industries among 30 industries, which have higher mean differences between two sample periods. Panel (b) shows bottom 7 industries have lower mean differences between two sample periods.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

period. Change in idiosyncratic risk varies widely from petroleum and natural gas industry (1.81), bituminous coal (1.24) and restaurant, hotels and lodgings (0.98) to steel (0.12) and food production (0.09). The results suggest that all industries have been effected by business shutdowns, social distancing and lower demand. The largest shift in idiosyncratic risk, associated with the petroleum and natural gas industry, is driven by plunging oil prices and uncertainty regarding the long-term effect of the shutdown on consumer demand for oil and gas. Ongoing reduced levels of travel further depress the demand for oil, restricting cashflow and potentially curtailing future drilling and production.

3.2. Regression results

The regression results reported in Table 5 suggest that daily changes in total risk can be explained by daily change in VIX, the Federal Target Rate and daily percentage of deaths and recoveries. In column (3), we find that total risk will increase by 0.002 for every one-unit increase in VIX and will increase by 4.03 per cent for every one per cent increase in percentage of deaths. Conversely, total risk will decrease by 0.153 per cent for every one per cent increase in FTR and will decrease by 1.30 per cent for every one per cent increase in percentage of recoveries. Total risk in the US stock market is more significantly impacted by both positive and negative COVID-19 reporting, rather than expected level of price fluctuation (ΔVIX) and monetary policy (ΔFTR).

For robustness, a regression analysis is run for each of the 30 industries. Table 6 summarizes the results for the top seven and bottom seven industries based on the magnitude of γ_3. All the industries are more sensitive to COVID-19 reporting than market

Table 5
Regressions of the daily changes in total risk for CRSP VW index returns on the changes in VIX and FTR, percent of deaths, and percent of recoveries.

Coefficients	Dependent Variable: Δ Risk (1)	(2)	(3)
Intercept	0.016***	0.004	0.011*
	(3.55)	(0.77)	(1.69)
Δ VIX	0.001	0.002**	0.002*
	(1.39)	(1.83)	(1.97)
Δ FTR	−0.186***	−0.157***	−0.153***
	(−4.47)	(−3.93)	(−3.89)
pDeaths		3.916***	4.03***
		(3.40)	(3.55)
pRecoveries			−1.30*
			(−1.85)
F-statistics	17.96***	17.44***	14.34***
Adj. R^2	0.30	0.38	0.40

This table summarizes the results for three regression model over the sample period from Jan. 02, 2020 to Apr. 30, 2020. The dependent variable is daily changes in total risk, Δ Risk. Explanatory variables are daily changes in VIX (ΔVIX), daily changes in federal fund target range (ΔFTR), percent of deaths, and percent of recoveries.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6
Regressions of the daily changes in total risk for the respective industry stock returns on the changes in VIX and FTR, percent of deaths, and percent of recoveries.

Industry	γ_0	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Panel A: Top 7 industries						
Petroleum and Natural Gas	0.049	0.006	0.049	18.831***	−4.711*	0.10
	(1.39)	(1.26)	(0.23)	(3.08)	(−1.74)	
Coal	0.044*	−0.005*	−0.048	8.285**	−3.68*	0.10
	(2.17)	(−1.97)	(−0.39)	(2.34)	(−1.68)	
Metal and Mining	0.018	0.006***	0.147**	7.364***	−1.795*	0.24
	(1.56)	(4.04)	(2.17)	(3.79)	(−1.69)	
Restaurants, Hotels, & Lodgings	0.040**	0.006**	−0.364***	7.316**	−3.458*	0.36
	(2.31)	(2.53)	(−3.50)	(2.46)	(−1.86)	
Aircraft, Ships, and Railroad Equipment	0.027**	0.006***	−0.102*	6.958***	−2.368*	0.34
	(2.22)	(3.82)	(−1.41)	(3.36)	(−1.84)	
Recreation (Games and Entertainments)	0.026**	0.007***	−0.200**	6.723***	−3.013**	0.42
	(2.02)	(4.15)	(−2.59)	(3.04)	(−2.19)	
Construction & Construction Materials	0.026**	0.006***	−0.140**	6.671**	−2.476*	0.39
	(2.22)	(4.08)	(−2.00)	(3.31)	(−1.98)	
Panel B: Bottom 7 industries						
Consumer Goods	0.017**	0.004***	−0.081*	4.484***	−1.687**	0.43
	(2.32)	(4.64)	(−1.87)	(3.61)	(−2.19)	
Tele-com & Broadcasting	0.017**	0.004***	−0.090**	4.480***	−1.897**	0.38
	(2.29)	(3.76)	(−2.02)	(3.49)	(−2.38)	
Health Care, Medical, Pharmaceutical Products	0.012*	0.004***	−0.104***	4.022***	−1.530**	0.47
	(1.89)	(4.76)	(−2.67)	(3.58)	(−2.19)	
Business Equipment	0.013*	0.004***	−0.079*	3.953***	−1.550**	0.39
	(1.87)	(4.24)	(−1.91)	(3.34)	(−2.11)	
Tobacco	0.013	0.002*	−0.127**	3.813**	−1.739*	0.21
	(1.33)	(1.81)	(−2.19)	(2.28)	(−1.67)	
Beer & Liquor	0.010**	0.002***	−0.007	3.044***	−1.182*	0.22
	(1.84)	(3.15)	(−0.23)	(3.11)	(−1.95)	
Food Production	0.009***	0.002***	−0.046	2.813***	−0.997**	0.30
	(1.86)	(2.87)	(−1.64)	(3.49)	(−1.99)	

This table summarizes the results of the following regression model for featured industries among 30 industries over the sample period from Jan. 02, 2020 to Apr. 30, 2020. In the model, $\Delta \text{Risk}_{i,t}$ represents change in total risk for industry *i*.
Model: $\Delta \text{Risk}_{i,t} = \gamma_0 + \gamma_1 \Delta \text{VIX}_t + \gamma_2 \Delta \text{FTR}_t + \gamma_3 \text{pDeaths} + \gamma_4 \text{pRecoveries} + \varepsilon_{i,t}$
*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

fundamentals. The coefficients of percentage of deaths and recoveries ranges from −0.997 to 18.331, whereas those of ΔVIX and ΔFTR range from −0.005 to 0.049. Daily COVID-19, both positive and negative news, is an important measure for estimating the change in total risk in the US stock market. Notably, the results show that daily negative COVID-19 news is more impactful than positive COVID-19 news since the coefficient for percentage of deaths is approximately at least two times greater than the absolute values for percentage of recoveries in every industry sector. This indicates an asymmetric impact of COVID-19 bad versus good news on volatility spillovers, positive news impacts volatility less than negative news during this systemic event, in line with Koutmos and Booth (1995).

4. Conclusion

We utilize the MS-AR (1) model to confirm a regime change in U.S. stock market volatility with the inception of COVID-19. Our results show significant increase in total risk for the US stock market. An examination of changes across 30 industries shows increases in total and idiosyncratic risk for all industries. Notably, we document significant increases in systematic risk for defensive industries, such as telecom and utilities, but decreases in systematic risk for aggressive industries, such as automobiles and business equipment. These results may stem from customers with lower/higher price elasticity, shielding/exposing firms to demand shocks. To understand what drives daily changes in volatility, total risk is regressed on economic indicators, identified as influential through ML selection methods and COVID-19 deaths and recoveries. Results show that changes in volatility are more sensitive to COVID-19 news than economic indicators. Additionally, the negative news regarding number of deaths is twice as impactful as positive news regarding recoveries suggesting a negativity bias. The market reaction to COVID-19 news exhibits a positive-negative asymmetry.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Al-Awadhi, A.M., Alsaifi, K., Al-Awadhi, A., Alhamaddi, S., 2020. Death and contagious infectious diseases: impact of the COVID-19 virus on stock market returns. J. Behav. Exp. Finance 27, 100326. https://doi.org/10.1016/j.jbef.2020.100326.

Albuquerque, R.A., Koskinen, Y.J., Yang, S. and C. Zhang, 2020. Resiliency of Environmental and Social Stocks: an Analysis of the Exogenous COVID-19 Market Crash. *European Corporate Governance Institute*, Finance Working Paper No. 676/2020. https://ssrn.com/abstract=3583611 or http://dx.doi.org/10.2139/ssrn.3583611.

Alfaro, L., Chari, A., Greenland, A.N. and Schott, P.K.2020. Aggregate and firm-level stock returns during pandemics in real time, *CEPR Covid Economics Review*, NBER Working Paper No. w26950. https://ssrn.com/abstract=3569414.

Ashraf, B.N., 2020. Stock markets' reaction to COVID-19: cases or fatalities. Res. Int. Bus. Finance 54, 101249. https://doi.org/10.1016/j.ribaf.2020.

Bai, Y., 2014. Cross-border sentiment: an empirical analysis on EU stock markets. Appl. Financ. Econ. 24, 259–290. https://doi.org/10.1080/09603107.2013.864035.

Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment. J. Financ. Econ. 104, 272–287. https://doi.org/10.1016/j.jfineco.2011.11.002.

Baker, S., Bloom, N., Davis, S.J., Kost, K., Sammon, M. and Viratyosin, T.2020. The unprecedented stock market impact of COVID-19. *CEPR Covid Economics Review*, NBER Working Paper No. w26945. http://www.nber.org/papers/w26945.

Chen, C.D., Chen, C.C., Tang, W.W., Huang, B.Y., 2009. The positive and negative impacts of the SARS outbreak: a case of the Taiwan industries. J. Dev. Areas 43 (1), 281–293.

Chen, M.H., Jang, S.S., Kim, W.G., 2007. The impact of the SARS outbreak on Taiwanese hotel stock performance: an event-study approach. Int. J. Hosp. Manag. 26 (1), 200–212. https://doi.org/10.1016/j.ijhm.2005.11.004.

Chen, M.P., Lee, C.C., Lin, Y.H., Chen, W.Y., 2018. Did the S.A.R.S. epidemic weaken the integration of Asian stock markets? Evidence from smooth time-varying cointegration analysis. Econ. Res. 31, 908–926. https://doi.org/10.1080/1331677X.2018.1456354.

Davison, C.2020. Stock returns, leverage, and the COVID-19 pandemic. Available at SSRN: 10.2139/ssrn.3627595.

Del Giudice, A., Paltrinieri, A., 2017. The impact of the Arab Spring and the Ebola outbreak on African equity mutual fund investor decisions. Res. Int. Bus. Finance 41, 600–612. https://doi.org/10.1016/j.ribaf.2017.05.004.

Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Finance Res. Lett. 35, 101512. https://doi.org/10.1016/j.frl.2020.101512.

Hamilton, J., Susmel, R., 1994. Autoregressive conditional heteroscedasticity and changes in regime. J. Econom. 64, 307–333. https://doi.org/10.1016/0304-4076(94)90067-1.

Haroon, O., Rizvi, S.A.R., 2020. COVID-19: media coverage and financial markets behavior—A sectoral inquiry. J. Behav. Exp. Finance 27https://doi.org/10.1016/j.jbef.2020.100343. 100343.

Heyden, K.J. and Heyden, T.2020. Market reactions to the arrival and containment of COVID-19: an event study. https://ssrn.com/abstract=3587497 or 10.2139/ssrn.3587497.

Ichev, R., Marinč, M., 2018. Stock prices and geographic proximity of information: evidence from the Ebola outbreak. Int. Rev. Financ. Analy. 56, 153–166. https://doi.org/10.1016/j.irfa.2017.12.004.

Koutmos, G., Booth, G., 1995. Asymmetric volatility transmission in international stock markets. J. Int. Money Finance 14, 747–762. https://doi.org/10.1016/0261-5606(95)00031-3.

Liew K., J., Mayster, B., 2018. Forecasting ETFs with machine learning algorithms. J. Alternat. Invest. 20 (3), 58–78. https://doi.org/10.3905/jai.2018.20.3.058.

Liu, H., Manzoor, A., Wang, C., Zhang, L., Manzoor, Z., 2020. The COVID-19 Outbreak and affected countries stock markets response. Int. J. Environ. Res. Public Health 17 (8), 2800. https://doi.org/10.3390/ijerph17082800.

Mohanty, S., Akhigbe, A., Basheikh, A., Kahn, H.U.R., 2018. The Dodd-Frank act and Basel III: market-based risk implications for global systemically important banks. J. Multinat. Financ. Manage. 47–48, 91–109. https://doi.org/10.1016/j.mulfin.2018.10.002.

Onali, E., 2020. COVID-19 and stock market volatility. SSRN: https://ssrn.com/abstract=3571453or 10.2139/ssrn.3571453.

Oreski, S., Oreski, G., 2014. Genetic algorithm-based heuristic for feature selection in credit risk assessment. Expert Syst. Appl. 41 (4), 2052–2064. https://doi.org/10.1016/j.eswa.2013.09.004.

Phan, D.H.B., Sharma, S., Narayan, P.K., 2015. Stock return forecasting: some new evidence. Int. Rev. Financ. Analy. 40, 38–51. https://doi.org/10.1016/j.irfa.2015.05.002.

Rizvi, S.A.R., Arshad, S., 2018. Understanding time-varying systematic risks in Islamic and conventional sectoral indices. Econ. Model. 70, 561–570. https://doi.org/10.1016/j.econmod.2017.10.011.

Wang, Y.H., Yang, F.J., Chen, L.J., 2013. An investor's perspective on infectious diseases and their influence on market behavior. J. Bus. Econ. Manage. 14, 112–127. https://doi.org/10.3846/16111699.2012.711360.

Zaremba, A., Kizys, R., Aharon, D.Y., Demir, E., 2020. Infected markets: novel Coronavirus, government interventions, and stock return volatility around the Globe. Finance Res. Lett. 35, 101597. https://doi.org/10.1016/j.frl.2020.101597.

Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 35, 101528. https://doi.org/10.1016/j.frl.2020.101528.